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SMART AGROFRIEND USING MACHINE LEARNING

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ABSTRACT

In today's rapidly evolving world, the agricultural sector is fundamental to ensuring food security, economic stability, and sustainable resource use. However, farmers often face significant challenges, including limited access to reliable labor, insufficient information on market trends, barriers to renting or purchasing essential agricultural equipment, and limited options for livestock trading. These issues directly impact productivity and income, often leading to suboptimal resource utilization and decreased farming efficiency.

I. INTRODUCTION

Addressing these challenges, the project titled **"Smart AgroFriend Using Machine Learning"** introduces an innovative solution designed to bridge these critical gaps. By leveraging the power of machine learning and digital tools, Smart AgroFriend provides farmers with a comprehensive platform that covers four key areas: **Labor-Farmer Connectivity, Equipment Rental or Purchase, Livestock Trade, and Crop Price Prediction.** This system empowers farmers to make informed decisions, optimize operations, and improve overall livelihoods.

SmartAgrfriend integrates features such as real-time labor matching, predictive crop market analytics, equipment recommendations, and an accessible livestock marketplace, enabling seamless agricultural operations. The machine learning model embedded within Smart AgroFriend, designed for crop price forecasting, provides farmers with insights based on historical market data, helping them anticipate price trends for a variety of crops. These functionalities create a digital ecosystem tailored to modern agricultural needs, aiming to increase productivity, encourage sustainable practices, and improve financial outcomes for farmers.

Through SmartCrop, farmers can access reliable data and resources that enable them to optimize productivity, reduce dependency on intermediaries, and promote a more resilient farming ecosystem. This digital platform not only serves as a practical tool for managing daily farming operations but also fosters a collaborative environment, paving the way for continuous learning, resource sharing, and future research in AgriTech.

1.2 Literature Survey:

1.2.1 Agriculture as a Vital Sector:

Agriculture is a vital sector that sustains global food security and economic growth. However, modern farmers encounter numerous obstacles, including the unpredictable nature of market prices, limited access to labor, and high costs of essential agricultural equipment. As the industry grows, these issues have intensified, emphasizing the need for efficient solutions. Various studies confirm that technological solutions can help mitigate these challenges by providing timely access to labor, predictive analytics for market prices, and streamlined resource management. By adopting digital platforms, farmers can better manage resources, predict market fluctuations, and improve farm profitability and sustainability.

1.2.2 Existing Studies on AgriTech Solutions:

A growing number of AgriTech solutions have sought to address these challenges. For instance, platforms like Hello Krushi provide digital resources to enhance farm management, including predictive models for crop prices and streamlined access to equipment. Other systems have implemented real-time job postings and labor matching to improve operational efficiency. However, many of these solutions often focus on single aspects of farm management, lacking an integrated approach. Smart AgroFriend aims to address this gap by combining labor connectivity, equipment rentals, livestock trading, and market predictions into a unified platform.

1.2.3 Machine Learning in Agriculture:

Machine learning has proven effective in various agricultural applications, particularly in market prediction and resource recommendation. Models such as Random Forest, Naive Bayes, and Linear Regression are commonly used to predict crop prices based on historical data, helping farmers make timely, data-driven decisions. Research indicates that advanced machine learning models can achieve high accuracy rates in price forecasting, which in turn, enables farmers to plan more effectively. These findings highlight the potential for machine learning to transform traditional agriculture, offering predictive insights that empower farmers to optimize crop production, manage resources, and improve profitability.

1.2.4 Gaps in Literature:

While AgriTech solutions continue to evolve, several gaps remain unaddressed. Many solutions focus on isolated aspects, such as labor access or price prediction, without offering a cohesive platform that addresses the full spectrum of farming needs. Furthermore, few platforms integrate machine learning for price prediction alongside resource and labor management. SmartCrop seeks to address these limitations by providing a fully integrated system that combines predictive analytics with essential resource access, creating a comprehensive platform designed to meet modern farmers' diverse needs.

1.3 Project Undertaken:

1.3.1 Problem Definition

To develop a machine learning-based system that enables farmers to efficiently connect with labor, rent or purchase equipment, trade livestock, and receive crop price predictions. Smart AgroFriend aims to simplify farm management and improve decision-making processes for farmers.

1.3.2 Scope Statement

1. **Inputs**: User-provided data on location, labor needs, equipment preferences, livestock details, and crop selection.

2. **Modules**:

- Labor-Farmer Connectivity with real-time job postings and matching
- Equipment Marketplace for rental and purchase with content-based filtering
- Livestock Trade platform with searchable tags and location filters
- Crop Price Prediction model based on machine learning algorithms

3. **Limitations**:

- Data accuracy is required for effective labor matching and equipment recommendations.
- Predictive model accuracy depends on comprehensive historical market data.

1.3.3 Objective of the Project

The primary objective of Smart AgroFriend is to empower farmers by providing a reliable, user-friendly platform that simplifies essential agricultural tasks. The system is designed to:

- Facilitate labor connections for efficient task management on farms.
- Offer predictive insights for crop prices to aid in financial planning.
- Streamline equipment and livestock transactions, making farming more accessible and profitable.

SmartCrop's machine learning model enhances its prediction capabilities, helping farmers stay ahead of market trends. By improving access to resources and predictive insights, SmartCrop fosters a sustainable and economically viable farming environment.

1.4 Organization of Report

The SmartCrop project report is divided into four main sections:

- **Chapter 1** provides an overview of the Smart AgroFriend project, including the background, problem statement, objectives, and scope.
- **Chapter 2** covers project planning and management, focusing on requirements specifications, cost estimation, and process modeling.
- **Chapter 3** demonstrates the project's technical aspects, including the mathematical models, feasibility analysis, and UML diagrams, providing a comprehensive view of system design and architecture.
- **Chapter 4** details the testing strategy and test cases, offering insights into the testing methodologies used to

ensure project functionality and reliability

II. PROJECT PLANNING AND MANAGEMENT

2.1 Introduction

This chapter outlines the project planning and management strategy for Smart AgroFriend. It also details the System Requirements Specification (SRS), serving as the foundation for effort estimation, project scheduling, and resource allocation.

2.2 System Requirement Specification (SRS)

2.2.1 System Overview

Smart AgroFriend is a comprehensive digital platform that leverages machine learning algorithms to enhance farm management. It addresses essential agricultural needs, including labor-farmer connectivity, equipment rental and purchase, livestock trading, and crop price prediction. The system is built for easy access across various devices, providing a unified platform that empowers farmers with decision-making insights and efficient resource allocation.

The main features of Smart AgroFriend include:

1. Cross-Platform Support: Available across devices and operating systems to ensure accessibility for all users.
2. Labor Connectivity: Farmers can post job listings, and laborers can browse opportunities by location and availability.
3. Equipment Marketplace: Enables farmers to rent or purchase agricultural equipment, with filtering options for preferences and content-based recommendations.
4. Livestock Trading Platform: A streamlined process for buying and selling livestock, with searchability by location and animal type.
5. Crop Price Prediction: Utilizes machine learning to forecast crop prices based on historical data, providing farmers with actionable insights for planning.
6. Data Integrity and Validation: Ensures data accuracy and completeness for seamless transactions and reliable recommendations.

2.2.2 Functional Requirements

- **Labor Connectivity**
  - Main Flow:
    - Farmers can create job posts specifying required skills, location, and compensation.
    - Laborers can view these listings and apply based on their availability and qualifications.
  - Exceptional Flow:
    - If any data is missing, the system will prompt the user for completion before posting.
    - Irrelevant or inappropriate data is flagged for correction.
- **Equipment Marketplace**
  - Main Flow:
    - Users can browse equipment available for rent or purchase and make reservations or payments.
    - Content-based filtering suggests equipment based on past user interactions.
  - Exceptional Flow:
    - Missing or incomplete equipment details will halt the listing process.
    - Users are notified if the equipment is unavailable at the selected time.
- **Livestock Trading**
  - Main Flow:
    - Farmers can post livestock for sale with detailed information, including type, age, health status, and location.
    - Buyers can filter searches by location, animal type, and other attributes.
  - Exceptional Flow:

- Listings with insufficient details are flagged, and users are prompted for additional information.
- The system auto-archives listings after a specific period to ensure relevance.

- **Crop Price Prediction**
  - Main Flow:
    - Historical crop data is processed to generate price forecasts using a machine learning algorithm.
    - Farmers receive updates on expected trends for selected crops, assisting in strategic planning.
  - Exceptional Flow:
    - If there is insufficient historical data for accurate forecasting, the system notifies the user with available information.

2.2.3 Non-Functional Requirements

- Response Time Smart AgroFriend processes data requests and generates recommendations within seconds, ensuring optimal user experience.
- System Availability: The system operates 24/7, accessible to all users for uninterrupted support.
- User-Friendly Interface: The intuitive interface facilitates easy navigation, immediate feedback, and smooth interaction.
- Inclusivity: Smart AgroFriend supports multiple platforms and devices, making it accessible for all farmers, regardless of their technical background.

2.2.4 Deployment Requirements

Operating and Deployment Environment for Smart AgroFriend:

- Architecture: Client-Server System
- Operating Systems: Windows or Linux
- IDE/Code Editor: Visual Studio Code, IntelliJ IDEA
- Programming Tools:
  - Backend: Node.js with Express for API handling
  - Machine Learning: Python, Scikit-Learn for algorithms like Linear Regression and Random Forest, NumPy, and Pandas for data handling
  - Frontend: Flutter for mobile access and responsive user experience
  - Database: SQL for relational data storage, Firebase for real-time communication
  - Recommendation System: Content-based filtering for personalized equipment suggestions

2.2.5 External Hardware Requirements

- Processor: Minimum Intel i3 or equivalent
- RAM: Minimum 4 GB RAM
- Storage: At least 10 GB for data storage and application usage
- Network: Stable internet connection for reliable access and data exchange

2.3 Project Process Modeling

Smart AgroFriend follows an Agile Development model, allowing for flexibility and adaptability to user feedback and changing requirements. Each feature is developed and tested incrementally, enabling efficient adjustments throughout the project lifecycle.

Regular team meetings ensure alignment on project goals, while continuous user feedback integration enhances the overall user experience. This iterative model allows for timely identification and resolution of issues, leading to a more robust product that better meets the needs of farmers and agricultural professionals.

2.4 Methodology

2.4.1 Data Collection and Preprocessing

The data collection process involves gathering relevant inputs across Smart AgroFriend's key features, including labor availability, equipment details, livestock data, and historical crop prices. Preprocessing ensures

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data consistency, handling missing values and performing scaling where necessary to improve model performance.

Preprocessed data is divided into training (80%) and testing (20%) subsets, allowing us to train the machine learning model on one set while evaluating performance with the other.

2.4.2 Feature Engineering

For improved performance, derived features are created. For example:

- User Preference: Derived from past interactions to optimize recommendations in the equipment marketplace.
- Crop Trend Analysis: Based on historical data to enhance the accuracy of price forecasting.

Feature selection is performed to identify critical attributes for each module, reducing complexity and enhancing model interpretability.

2.4.3 Price Prediction and Recommendation

- Price Prediction: Linear Regression and Random Forest algorithms analyze historical price data, providing reliable forecasts for various crops. Hyperparameter tuning through Grid Search ensures that the model achieves optimal performance.
- Content-Based Recommendations: Content-based filtering personalizes suggestions based on user preferences, matching equipment and livestock listings to individual needs. This personalized approach improves the system's usability and relevance.

2.4.4 Model Evaluation

Smart AgroFriend's prediction and recommendation models are evaluated using metrics such as accuracy, precision, and recall, ensuring high performance across modules. Confusion matrices and ROC curves provide insights into the model's ability to correctly classify recommendations and price predictions.

Additionally, feature importance analysis validates the feature engineering process, ensuring that the most relevant attributes contribute to the models' outcomes.

2.4.5 System Integration and Deployment

After developing the prediction and recommendation models, they are integrated into Smart AgroFriend's unified platform. The front-end interface allows users to easily access labor connections, equipment listings, livestock trading, and crop forecasts. A data processing pipeline ensures that new inputs are immediately incorporated into the system, providing timely and relevant recommendations.

2.4.6 Continuous Improvement

Smart AgroFriend is designed with a continuous improvement mechanism. Regular user feedback is collected to refine the system, and the machine learning model undergoes periodic retraining to adapt to new data and usage patterns. This iterative enhancement process ensures that Smart AgroFriend remains relevant and effective over time.

III. ANALYSIS AND DESIGN

3.1 Introduction

This chapter provides a detailed analysis and design of the Smart AgroFriend system, outlining the mathematical model, feasibility analysis, and system architecture, supported by relevant UML diagrams.

3.2 Mathematical Model

The Smart AgroFriend system can be represented as a closed system, defined as: S={Ip,Op,Ac,Su,Ex,Fa}S = \{ Ip, Op, Ac, Su, Ex, Fa \}S={Ip,Op,Ac,Su,Ex,Fa}

Where:

- **Ip** = Set of Inputs
- **Op** = Set of Outputs
- **Ac** = Set of Actions
- **Su** = Success States

- **Ex** = Exceptions
- **Fa** = Failure States
- **Ip:** Set of Inputs = {A1, A2, A3, A4, A5}
  - A1 = Job listings for labor
  - A2 = Equipment details for rental/purchase
  - A3 = Livestock details
  - A4 = Historical crop price data
  - A5 = User preferences
- **Op:** Set of Outputs = {Op1, Op2, Op3, Op4}
  - Op1 = Labor connections and job applications
  - Op2 = Equipment recommendations
  - Op3 = Livestock trading matches
  - Op4 = Predicted crop prices for planning
- **Ac**: Set of Actions = {A1, A2, A3, A4}
  - A1 = Collect and input relevant farming data (job listings, equipment, etc.)
  - A2 = Generate labor connections based on location and needs
  - A3 = Suggest equipment based on user preferences using content-based filtering
  - A4 = Predict crop prices using the Random Forest and Linear Regression algorithms
- **Su**: Set of Success States = {S1}
  - S1 = All inputs successfully processed, and relevant connections, recommendations, and predictions generated
- **Ex:** Set of Exceptions = {Ex1, Ex2}
  - Ex1 = Missing or incomplete data from user inputs
  - Ex2 = Inaccurate historical data affecting prediction results
- **Fa:** Set of Failures = {F1}
  - F1 = System or network failure during data processing or prediction generation

3.3 Feasibility Analysis

NP Problem: NP (Non-deterministic Polynomial time) problems are problems where solutions are computationally challenging to find but relatively simple to verify. In the Smart AgroFriend system, certain tasks like accurate forecasting of crop prices fall under this classification due to the complex, data-driven nature of agriculture and market trends.

NP-Hard Problem: A problem is NP-Hard if every problem in NP can be polynomial-time reduced to it, making it computationally intensive to solve within reasonable time for large inputs.

NP-Complete Problem: A problem is NP-Complete if it lies at the intersection of NP and NP-Hard, implying it is difficult both to solve and verify quickly as inputs grow.

Problem Statement

Smart AgroFriend is an integrated system that addresses various agricultural needs, including labor connectivity, equipment recommendations, livestock trading, and crop price prediction. These tasks require robust machine learning models and efficient algorithms to ensure responsiveness and accuracy, making it challenging but essential to implement scalable and feasible solutions.

Solution and Algorithms

The Smart AgroFriend system will utilize three core algorithms:

1. LSTM (Long Short-Term Memory): Used for time-series crop price prediction due to its ability to learn temporal dependencies in data.
2. Linear Regression: Employed for simpler, real-time predictions in situations with fewer features or where linear relationships suffice.

3. Content-Based Filtering: Used for equipment recommendations, matching items based on user profiles and previous interactions.

Time Complexity:

- LSTM (Long Short-Term Memory):
  - The time complexity of LSTM is O(T×D×H)O(T \times D \times H)O(T×D×H), where:
    - TTT = Time steps in the input sequence,
    - DDD = Dimension of the input features,
    - HHH = Number of hidden units.
  - Given its recurrent nature, LSTM has a higher time complexity compared to linear models but is well-suited for time-series forecasting. For crop price prediction, LSTM's ability to capture historical dependencies enables it to provide accurate forecasts, even for complex and long-term patterns.
- Linear Regression:
  - The time complexity of training Linear Regression is O(N×p)O(N \times p)O(N×p), where:
    - NNN = Number of samples,
    - ppp = Number of features.
  - This makes Linear Regression highly efficient for real-time processing, ideal for scenarios where the relationship between variables is linear or only a small number of features are involved.
- Content-Based Filtering:
  - The complexity for content-based filtering largely depends on user-item comparisons, which is close to O(N)O(N)O(N) for a single user recommendation, where NNN represents the number of items.
  - This near-linear time complexity ensures recommendations are responsive and quickly accessible to users, even as the number of items or users grows.

Space Complexity

- LSTM (Long Short-Term Memory):
  - LSTM has a space complexity of O(T×H+H2)O(T \times H + H^2)O(T×H+H2), where:
    - TTT = Number of time steps,
    - HHH = Number of hidden units.
  - This complexity reflects the memory required to store cell states, making LSTM relatively memory-intensive, though manageable with efficient data handling.
- Linear Regression:
  - With a space complexity of O(p)O(p)O(p), Linear Regression is memory efficient, requiring only enough space for feature storage and coefficient calculations.
- Content-Based Filtering:
  - The space requirement for content-based filtering grows with the number of user and item profiles. Efficient storage methods like indexing and caching help mitigate storage requirements, making this method scalable in a growing system.

Feasibility Analysis Summary

The choice of LSTM, Linear Regression, and content-based filtering balances computational demands with real-time capabilities, making the Smart AgroFriend system feasible and efficient:

1. LSTM is feasible for crop price forecasting given its proficiency in handling time-series data. The higher complexity is justified by the value of accurate, long-term predictions for farmers.
2. Linear Regression supports simpler, faster predictions, making it an ideal backup for real-time scenarios where linear relationships are sufficient.
3. Content-Based Filtering is computationally lightweight for real-time equipment recommendations, ensuring a smooth user experience even as the number of users and items increases.

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Overall Project Complexity:

The Smart AgroFriend project is classified as NP-Hard due to the intricate nature of agricultural requirements, user personalization, and market prediction. However, by leveraging efficient algorithms and memory-optimized techniques, the system remains responsive and capable of scaling with the growth of user data.

3.4 Source code And Outputs

Folder Structure:

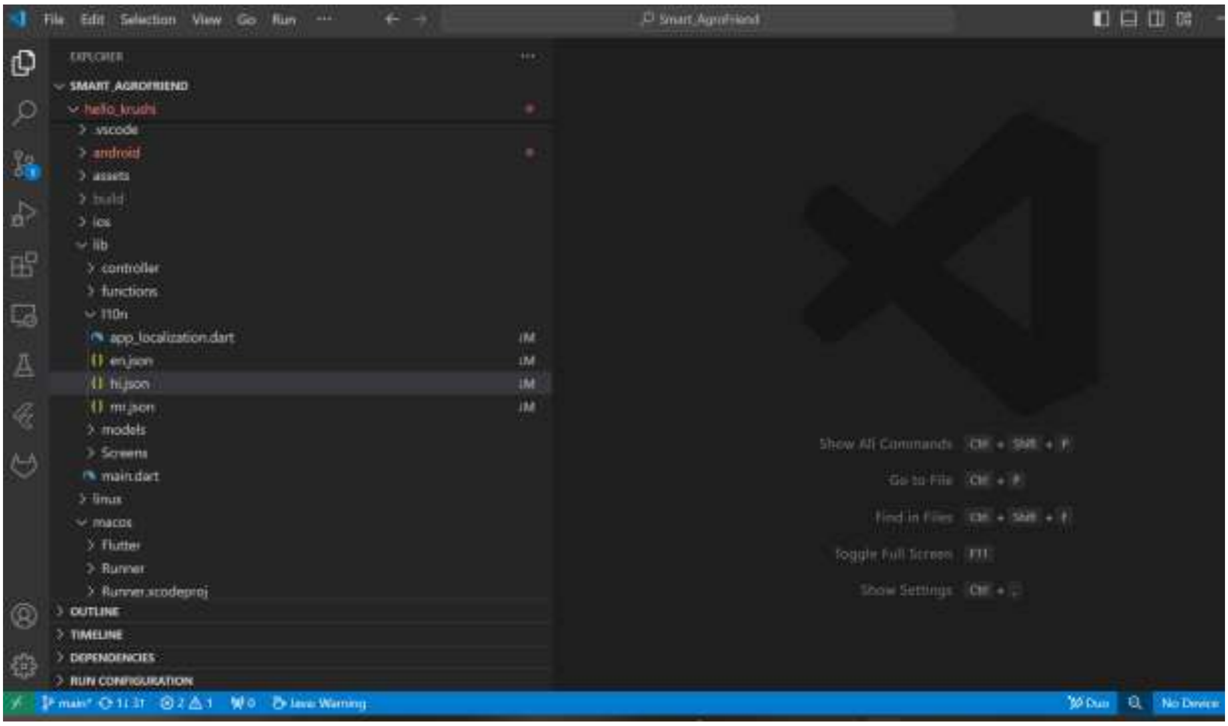

Fig 3.1:

Main file

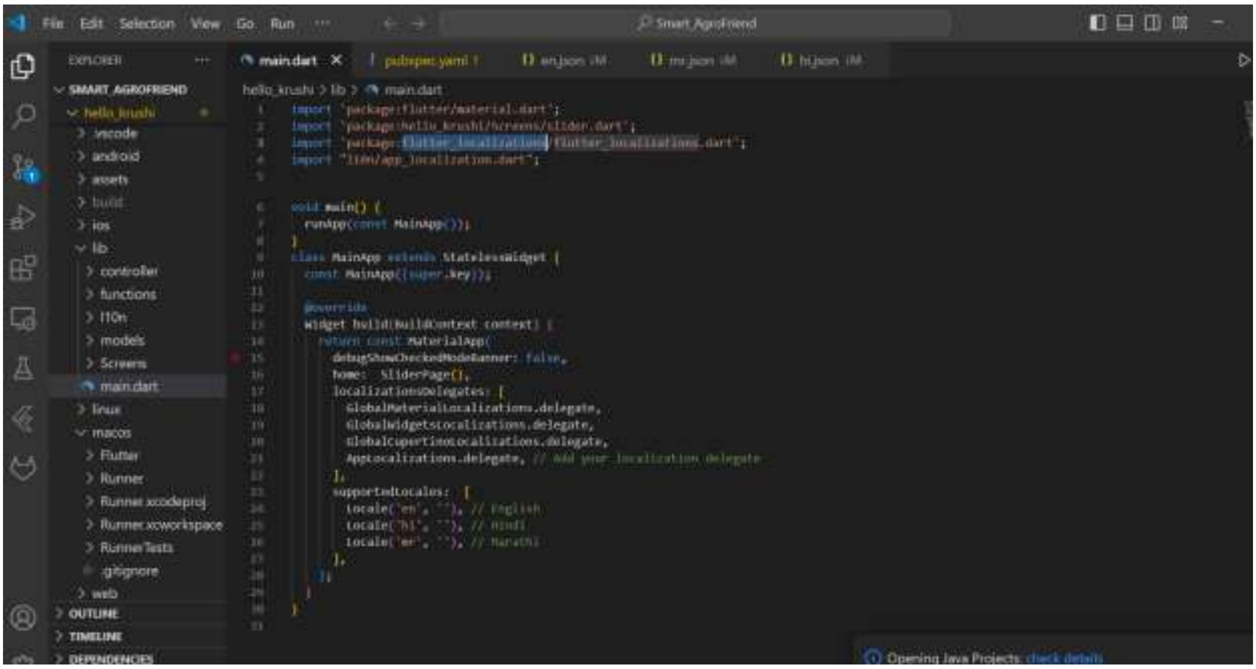

Fig 3.2:

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Home page

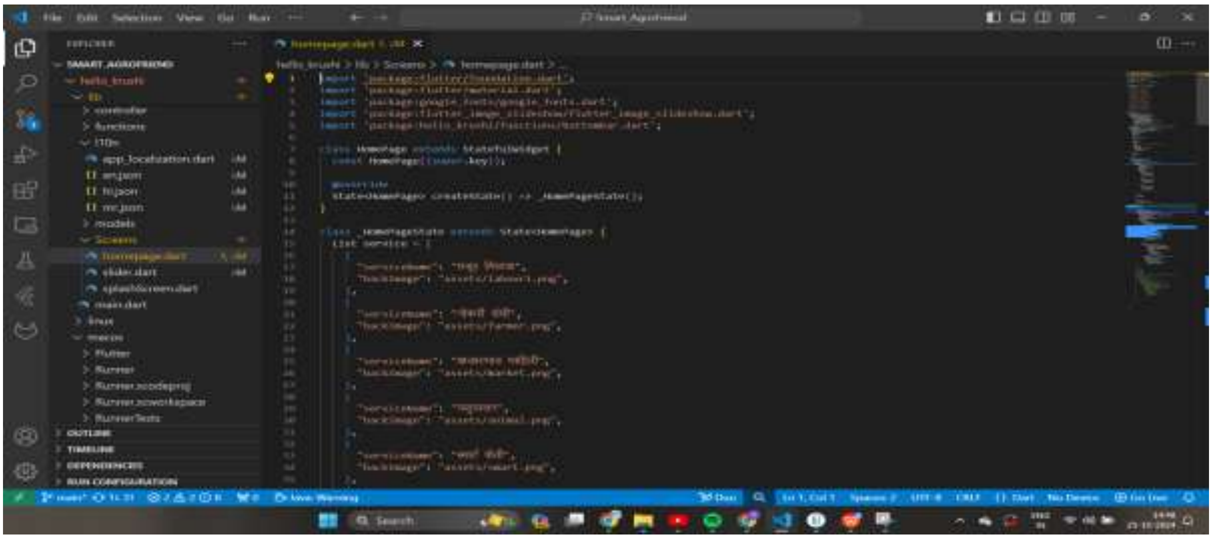

Fig 3.3:

Splash screen

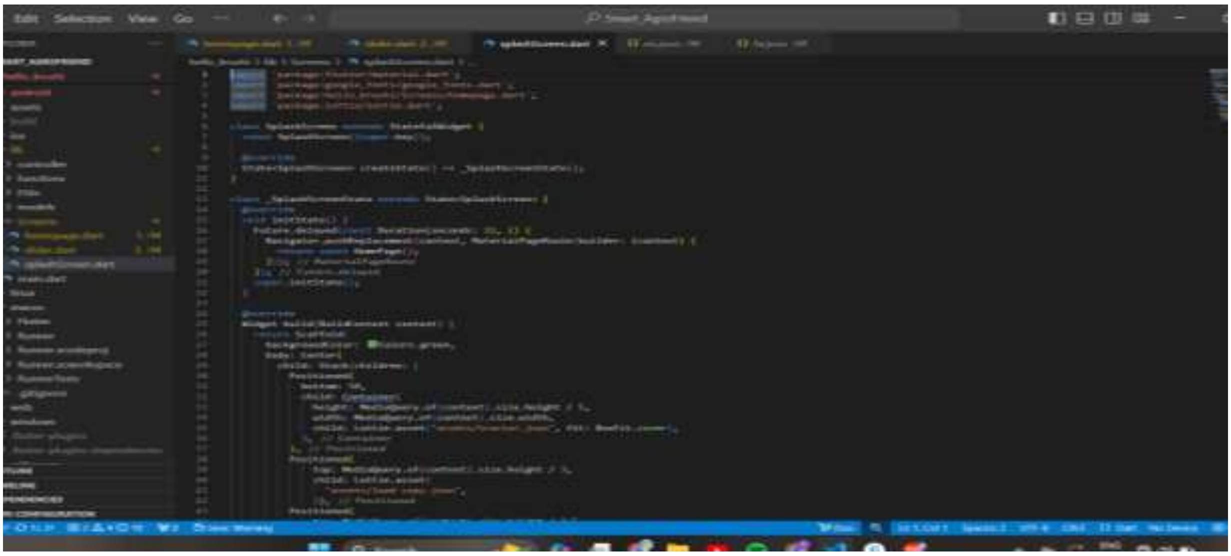

Fig 3.4:

Output

Fig 3.5:

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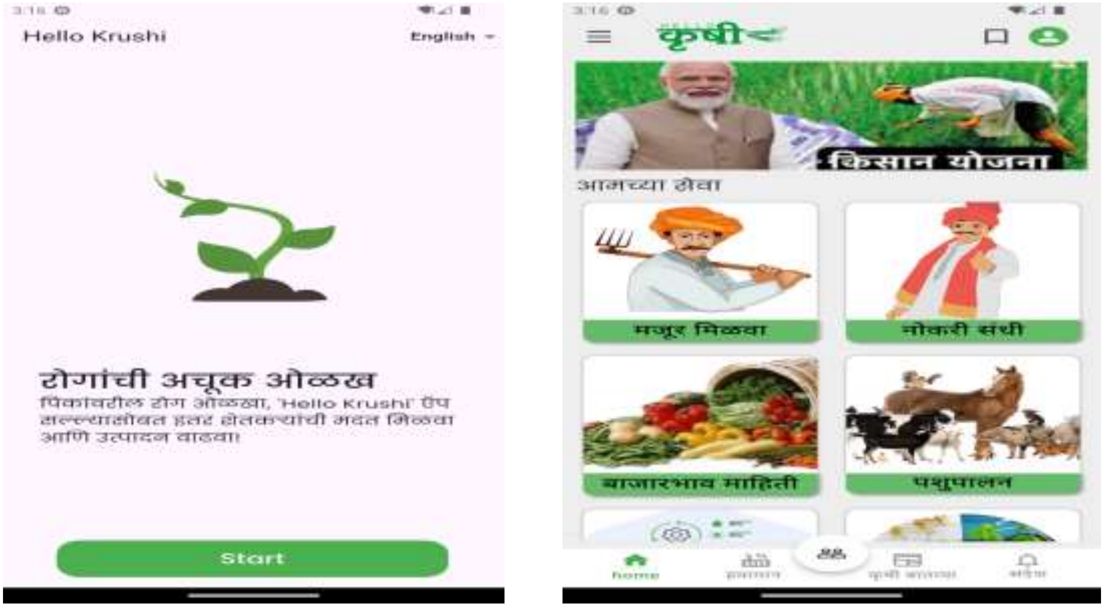

Fig 3.6:

3.5 UML Diagrams:

3.5.1 Use Case Diagram:

This use case diagram is used to determine the flow of the system. The user and the server are the actors in this scenario. After the home page is loaded, the user selects one of the features of the application. after selection of the features, the system asks for the text to be performed the function upon. The system then processes the text and tokenizes it, to give the required output.

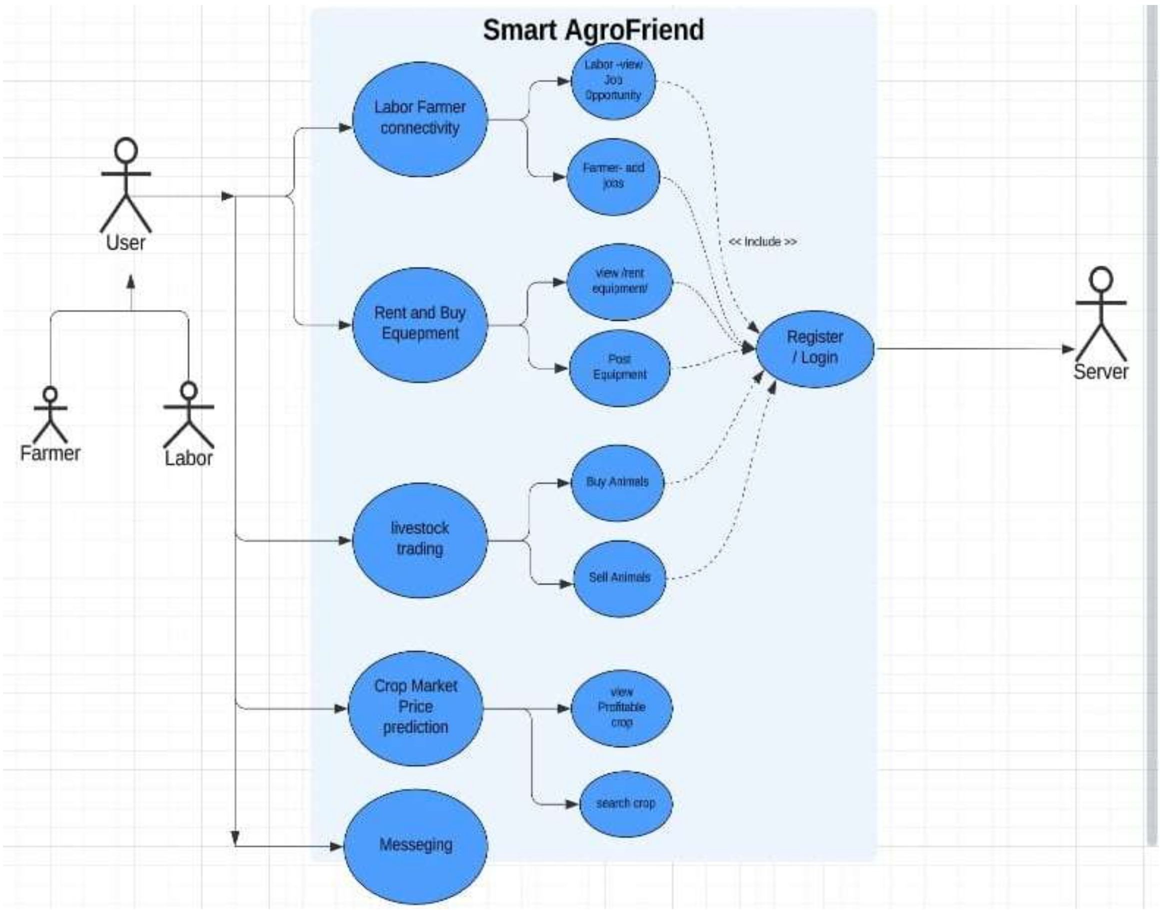

Fig 3.7: Use Case Diagram

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3.5.2 Activity Diagram:

Activity diagram is essentially an advanced version of flow chart that modeling the flow from one activity to another activity. Activity Diagrams describe how activities are coordinated to provide a service which can be at different levels of abstraction.

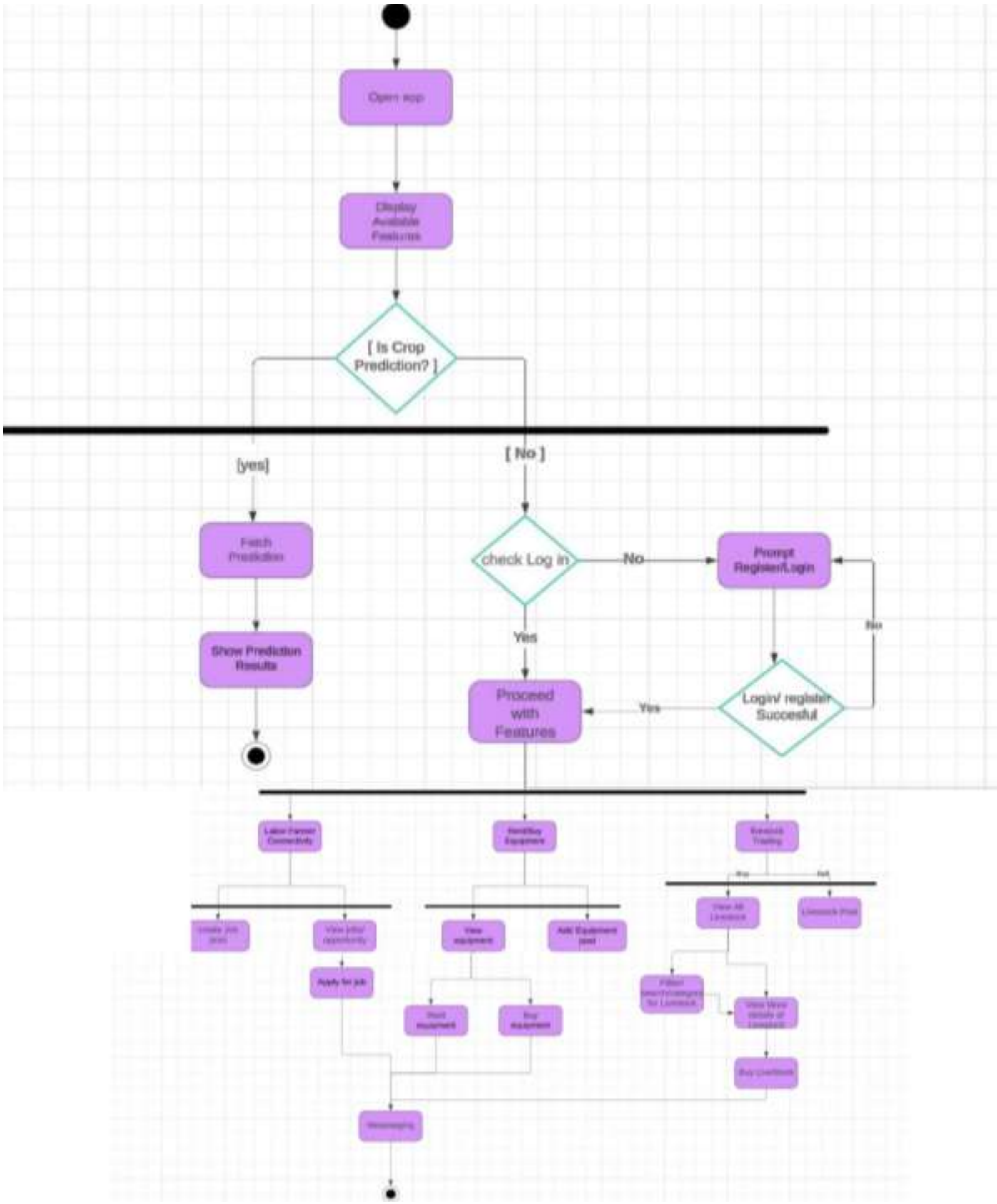

Fig 3.8: Activity Diagram

3.5.3 Sequence diagram

System flowcharts are a way of displaying how data flows in a system and how decisions are made to control events. To illustrate this, symbols are used. They are connected to show what happens to data and where it goes. Similarly, here we see the function illustrated in the diagram, and the corresponding functions are performed for them.

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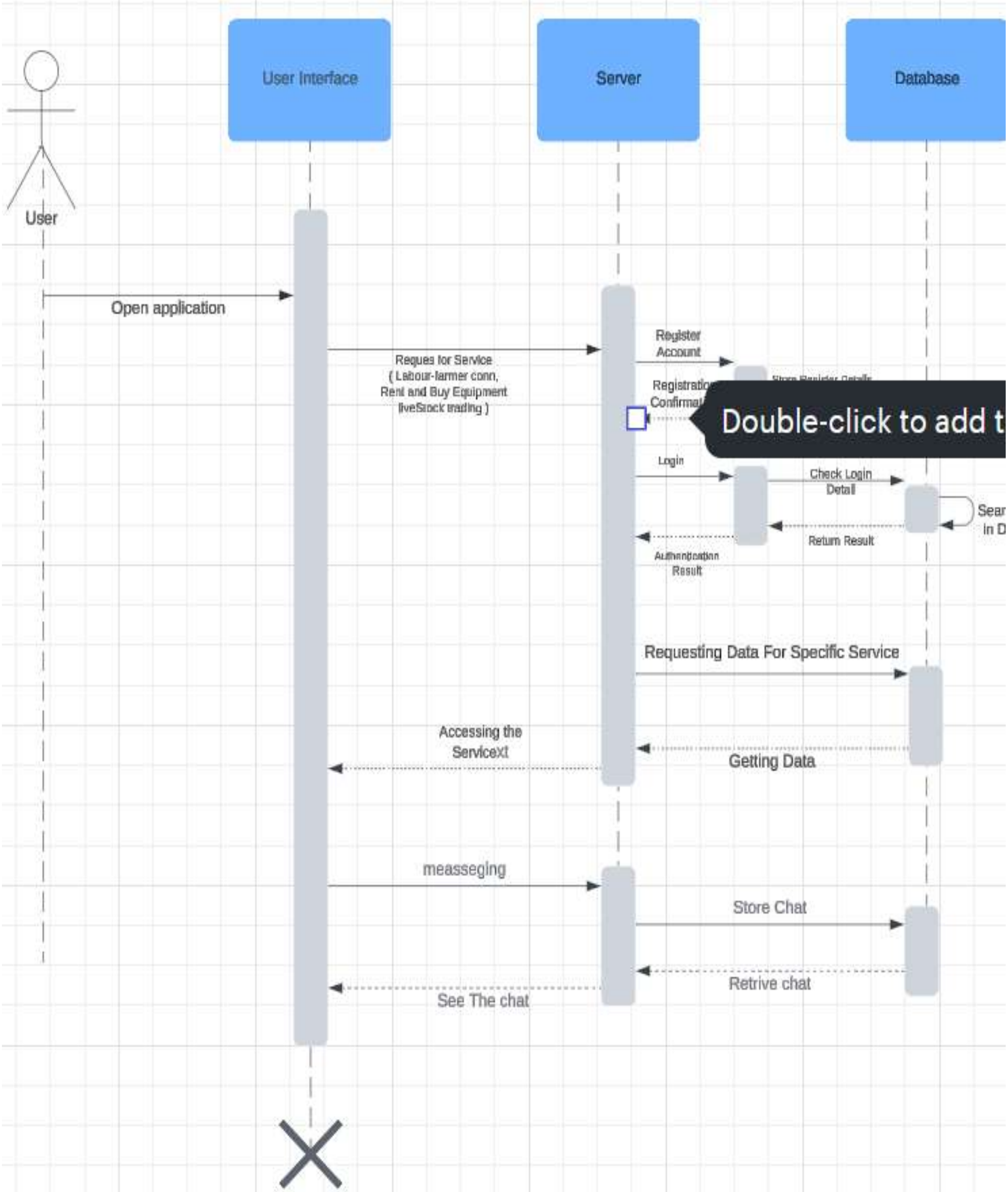

Fig 3.9: System Sequence Diagram

3.5.4 Class Diagram

The Class Diagram provides an overview of the structure of the Multi-level Stress Classification System by illustrating its main classes and their relationships. Key classes include User, which encapsulates user data and sleep parameters;

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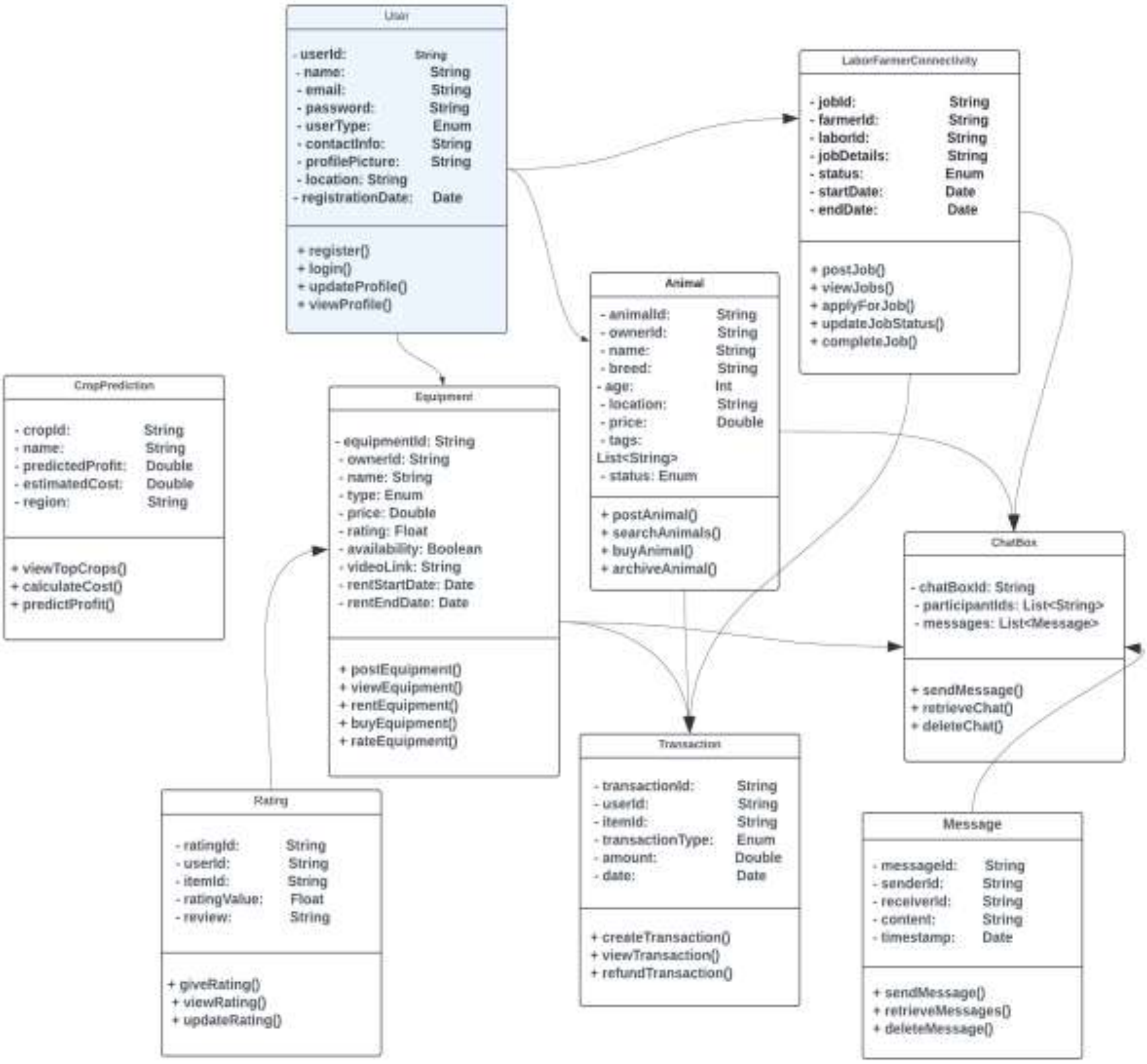

Fig 3.10: Class Diagram

IV. CONCLUSION

The Smart AgroFriend application is a comprehensive solution designed to address key challenges faced by farmers, leveraging technology to improve agricultural productivity and sustainability. By providing models for laborer-farmer connections, farm equipment marketplace, and crop market price predictions, the app empowers farmers to make informed decisions and enhance their efficiency. The inclusion of a pet animal marketplace adds further value, while the upcoming chat feature will enable real-time communication, fostering better collaboration between users.

The use of regex and similarity algorithms to match laborers and farmers based on location and skills ensures that resources are allocated effectively. Additionally, the Pik Margadarshan model offers valuable insights into crop selection, helping farmers adapt to changing weather patterns and market trends. Overall, Hello Krushi is a vital tool that supports farmers by connecting them with resources, information, and support, making a positive impact on the agricultural sector.

V. FUTURE SCOPE

1. Feature Expansion:

- Introduce additional features such as weather forecasting, pest and disease management tools, and educational resources for best agricultural practices.

2. Geographical Expansion:

- Expand the platform to serve farmers in different regions and countries, adapting the app to local agricultural practices, languages, and market dynamics.

3. Financial Services Integration:

- Collaborate with financial institutions to offer microloans, insurance products, and savings plans tailored to the needs of farmers, promoting financial stability and growth.

4. Data Analytics and Insights:

- Utilize data analytics to provide personalized insights and recommendations for farmers based on their activity and market trends, helping them optimize their farming strategies.

VI. REFERENCES

[1] Monali Paul, Ashok Verma, "Analysis of crop yield rates using data mining techniques to increase the yield rates of farmers", 2015 International Conference on Computational Intelligence And Communication Networks https://ieeexplore.ieee.org/document/7546199

[2] Sharma, R. (2020). Empowering farmers through technology. Journal of Farm Management, 25(1), 37-45. https://doi.org/10.1108/JFM-09-2020-0152

[3] Kaur, A., & Singh, R. (2021). The impact of e-commerce on agriculture. Journalof Rural Studies, 85, 171-183. https://doi.org/10.1016/j.jrurstud.2021.05.001

[4] Kumar, S., & Singh, A. (2019). Role of ICT in enhancing agricultural productivity. International Journal of Information and Education Technology, 9(8), 576-581.
https://doi.org/10.18178/ijiet.2019.9.8.1255

[5] Ranjan, R., & Sahu, R. K. (2021). Mobile apps for agriculture: A review. Journal of Agricultural and Food Information, 22(2), 134-152. https://doi.org/10.1080/10496505.2021.1931976

[6] Sahu, P. K., & Mohanty, S. (2020). The future of agriculture: A digital perspective. Agricultural Economics, 51(3), 457-469. https://doi.org/10.1111/agec.12539

[7] Sharma, R. (2020). Empowering farmers through technology. Journal of Farm Management, 25(1), 37-45. https://doi.org/10.1108/JFM-09-2020-0152

[8] Abdullah Na, "An IoT based system for crop monitoring", 2016 International Conference of Information Technology.Awanit Kumar, "Prediction of crops using K-Means .
https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=9410627

[9] D. Elavarasan and P. M. D. Vincent, ''Crop yield prediction using deep reinforcement learning model for sustainable agrarian applications,'' IEEE Access, vol. 8, pp. 86886–86901, 2020.

[10] J. Huang, J. L. Gómez-Dans, H. Huang, H. Ma, Q. Wu, P. E. Lewis, S. Liang, Z. Chen, J.-H. Xue, Y. Wu, F. Zhao, J. Wang, and X. Xie, ''Assimilation of remote sensing into crop growth models: Current status and perspectives,'' Agricult. Forest Meteorol., vols. 276–277, Oct. 2019, Art. no. 107609.

[11] S. Li, S. Peng, W. Chen, and X. Lu, ''INCOME: Practical land monitoring in precision agriculture with sensor networks,'' Comput. Commun. vol. 36, no. 4, pp. 459–467, Feb. 2013. [4] X. E. Pantazi, D. Moshou, T. Alexandridis, R. L. Whetton, and A. M. Mouazen, ''Wheat yield prediction using machine learning and advanced sensing techniques,'' Comput. Electron. Agricult., vol. 121, pp. 57–65, Feb. 2016.